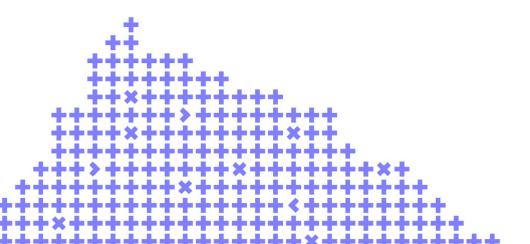
Machine Learning in the audio domain

When the neural network is overkill or where are the limits of lightweight models







Roman Smirnov

Machine Learning Engineer

- 1 year at Exness
- 7 years as an MLE/Tech Lead at Skyeng & MSU Labs

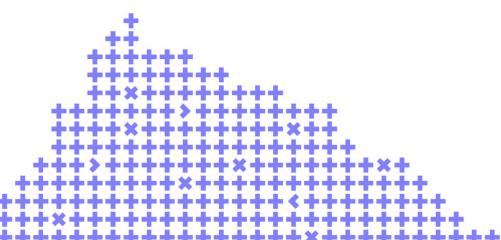






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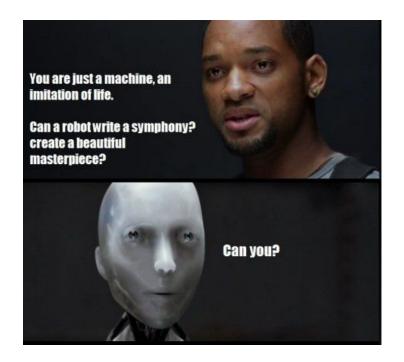
- Audio domain
- Problem statement
- Audio-domain tasks
- Experiments & Business
- Training process
- Results
- Business outcomes



Audio domain

Analyzing sounds using neural networks

- Call Centers
- Virtual Assistants
- Speech and music generation





Problem Statement



Data modality and SotA

When working with media data, we usually use large neural networks.

But:

- They are resource-heavy
- They are slower than light models

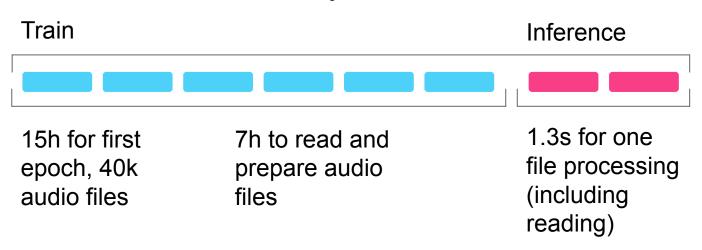
Usually it is **Transformers models**





Time for SotA

It takes **LONG** time to train SotA model for the task we'll discuss today



GPU: RTX 3090Ti, 24GB



Audio-domain tasks

Understanding and Generation



Understanding (Classification)

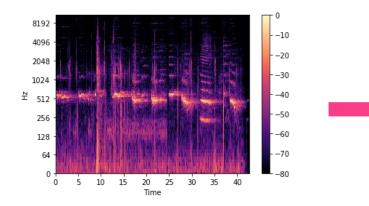
- Classification, e.g. emotions classification
- "Token classification"—voice activity detection
- Speaker separation, user verification
- Automatic Speech Recognition (ASR)

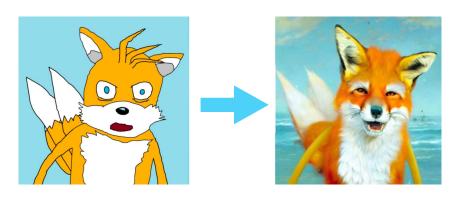




Generation

- Voice cloning
- Text to speech
- Speech and music generation







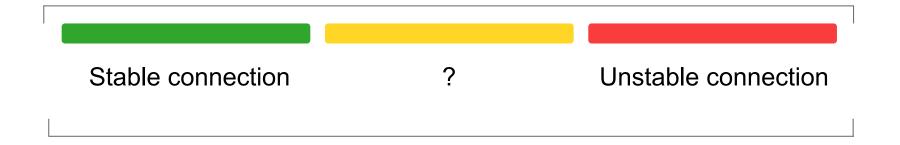


Experiments & Business



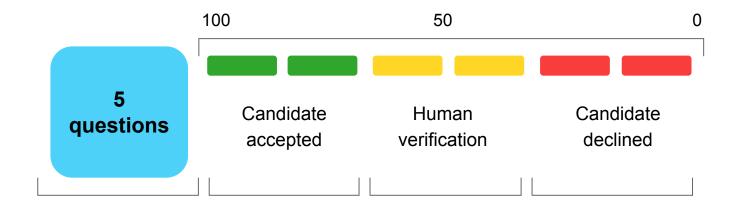
Classification

Evaluation of the call quality for the call center:



Regression

Interviewing a candidate for an English Teacher position

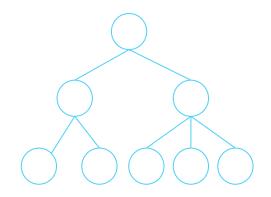


Fluency and pronunciation are evaluated separately using 5-points-scale

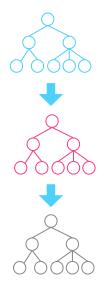
Gradient Boosting on Decision Trees (GB on DT)

- Fast
- Work on statistics aggregates of audio
- But is it accurate?

Single Decision Tree



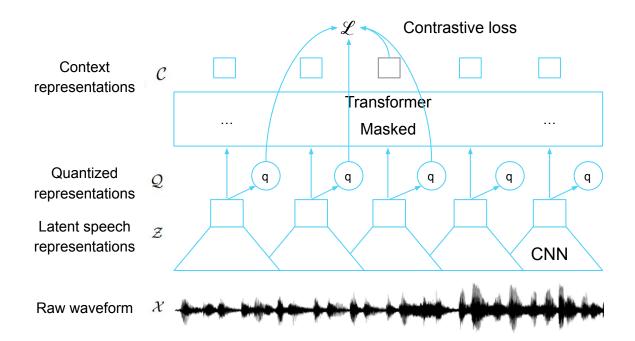
Gradient Boosted Trees





Wav2Vec2

- SotA for speech recognition
- Transformer model
- CNNs allows to encode local features
- But is it fast?



Training Process



Preprocessing

For GB on DT

- Collect amplitude and melspectrograms statistics
- Mean, median, min, max, std, kurtosis, skew... over mel for every frequency and raw wav

- Resample to 16kHz
- Just truncation

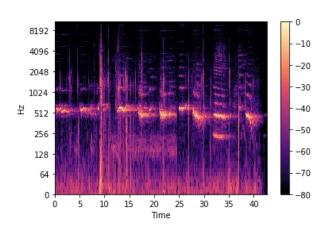


What is melspectrogram?

Raw audio



Melspectrogram



Training

For GB on DT

- Cathoost
- Small trees (depth 6)
- 100-10000 iterations

- Wav2Vec2 base
- Freeze feature encoder
- Learning rate schedulers
- 10 epochs



Time metrics. Classification

For GB on DT

- Train: 45 min to read data
- 0.5s to train on GPU
- 5k audio-files
- Inference: 5 files, 2s to read data, 0.1s to inference on CPU

- Train: 45 min to read data
- 5h to train on GPU (10 epochs)
- 5k audio-files, batch size 6
- Inference: 5 files, 2s to read data, 105s to inference on CPU



Time metrics. Regression

For GB on DT

- Train: 7h to read data
- 5 min to train on GPU
- 40k audio-files
- Inference: 5 files, 2s to read data, 0.1s to inference on CPU

- Train: 7h to read data
- 90h to train on GPU (10 epochs)
- 40k audio-files, batch size 6
- Inference: 5 files, 2s to read data, 105s to inference on CPU



Results

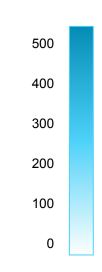


Results. Classification task

Natural imbalance!







GB on DT

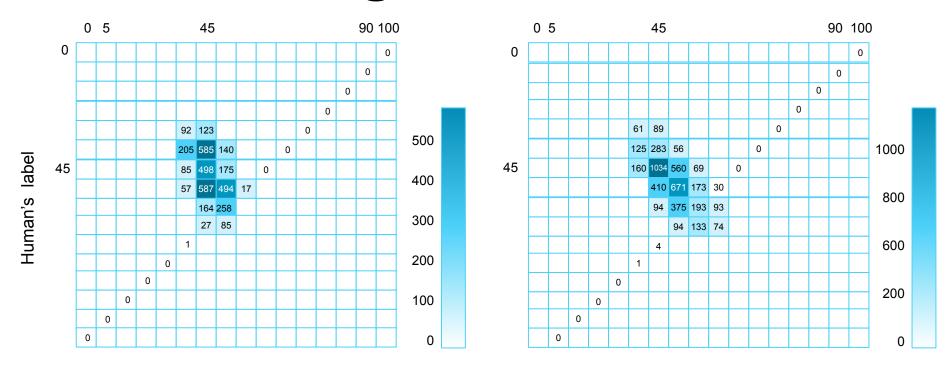
Models label

Models label

Wav2Vec



Results. Regression task



GB on DT

Model's label

Model's label

Wav2Vec



Business Outcomes



Outcomes

Time and \$ / accuracy trade-off

- We took GB on DT for classification
- We took Wav2Vec2 for regression

Where are the limits and what is overkill?



HEINLEY



Thank you for your attention!

Vote for my talk











